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Cervical Cancer Prediction Using Deep Learning

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Abstract- Given that gynecological cancers are among the most frequently diagnosed cancers, they pose a serious public health concern for women. Many women have a tendency to report their cancer at advanced stages in undeveloped countries with little cancer awareness programs, such as India, inconsistent pathology, and insufficient screening facilities, which negatively affects their prognosis and clinical outcomes. While cervical cancer continues to be second-most prevalent cancer after breast cancer, ovarian cancer is becoming more common in Indianwomen. Smoking, oral contraceptives, HPV (Human Papilloma Virus), and multiple pregnancies are just a few of the many causes of cervical cancer. Through early detection Adult women can avoid cervical cancer by getting timely treatment and taking tests like the PAP and HPV tests. PAP and HPV tests can detect.

Key Words- Machine Learning (ML), Convolution Neural Network (CNN), DeepLearning, Cervical Cancer.

I. INTRODUCTION

The most normal form of cancer in women, cervical cancer is brought on by abnormal cell growth in the cervix and has the potential to spread to other body organs. While there are typically no symptoms at first, later symptoms could include abnormal vaginal bleeding and pelvic pain. Cervical cancer is significantly more likely to occur in people who have certain types of the Human Papilloma Virus (HPV) infection, as well as in people who smoke cigarettes both actively and passively. Loss of appetite, weight loss, fatigue, back pain, leg pain, swollen legs, and vaginal bleeding are some of the symptoms of cervical cancer. In rare circumstances, the virus may spread to the liver, lungs, and bones. Cervical cancer can spread to nearby vaginal and various other uterine structures.

II. LITERATURE SURVEY

An automated computer based technique has been a reliable method [1] as cervical cancer is more common in women and worldwide it is most feared disease. Due to abnormal growth in the cervix cells, cervical cancer occurs and slowly it also spreads to the other organs of human body. Numerous factors, including the human papillomavirus, birth control pill use, smoking, and others, contribute to the development of cervical cancer. Cervical cancer does not initially exhibit any symptoms. However, if it is discovered earlier, it can be successfully treated. Many computer vision-based methods have been developed recently to recognize the stages of cervical cancer. The development of cervical cells out of control leads to cervical cancer because these cells do not die but instead continue to divide. According to the literature, cervical cancer is brought on by the HPV virus, smoking, a weakened immune system, among other things. By detecting cervical cancer in its early stages using the Pap smear test, the death rate from the disease is now significantly lower. Here, image processing methods are suggested to find cervical cancer early [2] as the most prevalent cancer among females is cervical cancer. It is born in the cervix. Primary surgery, primary radiotherapy, chemotherapy, and combination therapy are a few examples of the various treatments. While there are many methods for diagnosing cervical cancer, the crucial ones include biopsies, LBC tests, HPV tests, Pap smears, and various screening methods. The use of morphological image processing techniques has enabled the automatic detection of cervical malignant growth cells. Cervical cancers are manually screened using the Pap test and LCB test, which do not provide accurate classification results in classifying the normal and uncommon cervical cells inside the cervix region of the female reproductive system.

The paper [3] proposed here is Cervical Cancer Diagnosis using Cervix Net - A Deep Learning Approach. Cervical cancer is caused due to the Human Papilloma Virus (HPV) It causes cells around the cervix to develop abnormally. Thanks to widespread HPV testing of women, the mortality rate has dropped in industrialized countries. In order to select the appropriate course of therapy, we describe a unique CervixNet approach that conducts image enhancement on cervigrams before segmenting, classifying, and labelling the region of interest (RoI). The Deep Learning techniques used in biological imaging are the inspiration for this methodology.

For the classification challenge, it is advised to apply the cutting-edge Hierarchical Convolutional Mixture of Experts (HCME) method. Given that the overfitting issue may be resolved by HCME, short datasets represent a basic concern in the area of biomedical imaging. With a kappa score of 0.951 and accuracy of 96.77% accessible Kaggle datasets from Intel and Mobile-ODT. As a consequence, the outcomes support our strategy for offering first-level screening at a reasonable price. Image enhancement, role extraction, and the suggested RoI classification algorithm

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are all parts of the CervixNet technique. Here, Machine Learning approach [4] emphasizes the cutting-edge notion of utilizing a bidirectional filter for picture pre-processing. In this further, they have carried it out in the following steps: they have gathered the DATASET from HOSPITAL DENMARK from the Pap-Smear test, then the images are gone through the Pre-processing with filtering using Bilateral filter on the basis of filtration next they have segmentation process in which they have extracted the part that is used for the further detection (or study), followed by feature extraction where the useful data from microscopically observed is taken for the class. It is suggested that the colposcopy image is a crucial tool for early cancer diagnosis using the deep learning approach [5].

The transition zone colposcopic examination (TZ) is required for the evaluation and identification of patients with abnormal cytology who require additional treatment or follow-up. For the purpose of diagnosing the type of cervical cancer using colposcopic pictures, a new deep learning architecture called CYENET is presented. The oversampling technique balances the image collection to enhance the classification outcomes. In this study, two models are provided. One is utilizing the VGG19 architecture and a transfer learning approach. The other is a specialized brand-new model called CYENET for classifying the cervical cancer type using the dataset of ODT colposcopy images. Both the models are evaluated using classification accuracy, sensitivity, specificity, Cohen's Kappa score, and F1-measure. The classification accuracy for VGG19 was 73.3%. Relatively satisfied results are obtainedfor VGG (TL).

III. PROPOSED SYSTEM

A model for a data system that is far-reaching, including the origins of knowledge and utilitarian sections. In terms of requirements, this model shows a calculated framework that considers screening modalities, accessible information, level of computerization, equipment and programming, and levels of human and financial resources as being staged regularly after a period of time. The fundamental idea behind CNN is the automatic segmentation and pixel masking of each picture object.

A more condensed version of the VGG network family is used to discern between the effects of segmentation. A convolutional neural network (ConvNet) is a deep neural network. It is composed of a number of sequential layers, including convolutional, non-linear, and pooling layers, followed by one or more completely connected convolutional layers. The raw pixel values of an image are used as the convolutional network's input. Some neurons in the output layer were ready. Each neuron's target class corresponds to the output layer. Three neurons make up the output layer of the convolutional neural network, each of which corresponds to one of the three types of cervix, Type 1, Type2, and Type 3. Errors are eliminated using the ConvNet's weights (W), which use a back propagation technique from the classification layer. Transfer learning is applied to the Mask CNN weights trained using the dataset during the segmentation training phase, as shown in Figure 2.1. The proposed methodology's schematic block diagram is shown in figure 1.2.

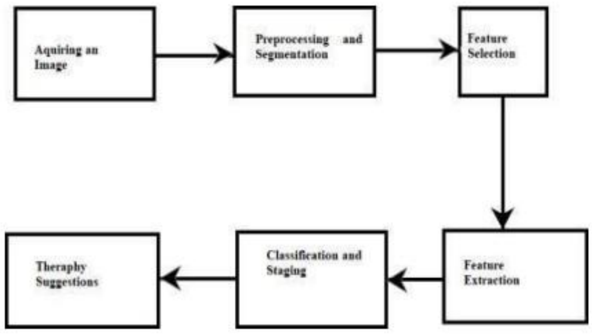

Fig 1: Block diagram of proposed system.

IV.IMPLEMENTATION

1. Image Dataset/Collection The selected dataset consists of three subgroups and contains around 6734 pictures were gathered from Mobile ODT and Intel. First, the images were divided into two categories: "Sharp" and "Not Sharp." Out of a total of 6734 photographs, 1981 were labeled as "Not Sharp" and 4753 as "Sharp". This denotes semantically focused in relation to the classes.

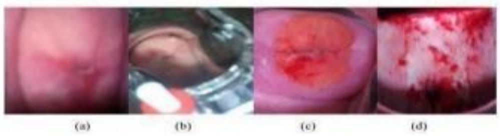

Fig 2: Instances of MobileODT (EVA) images. (a) & (b)are marked as "Not Sharp", (c) & (d) are named as "Sharp"

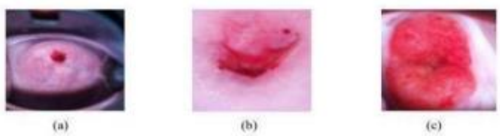

Fig 3: (a) Squamous (Type 1), (b) Adenocarcinoma (Type2) (c) Adenosquamous Carcinoma (Type 3)

2. Image Preprocessing The picture region is chosen by choosing the RoI of the image that contains all of the biomedical characteristics. The smaller pieces are then employed for the correct classification of the desired region after the features from the photos have been extracted. JPG array-formatted photographs can be found in the collection. Each image has an image structure of 2043*1536 pixels. Additionally, we divided each image into 6 squares with dimensions of 2043*1362 each, and then we fixed the images by resizing them to227*227 pixels. 2.3 Data

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Augmentation This is a technique for creating an exact assessment model. To divide the information acquired into training and testing data, it is necessary to select a.

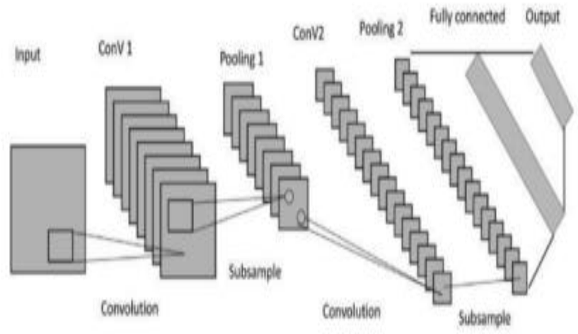

Fig 4: The architecture of CNN

model aptitude metric, assess the model, and develop a template or execution floor. Here, edge framing with the Gaussian High Pass channel is used to show off the image quality before the relevant area is found and the background is eliminated. This technique is widely utilized and makes use of TensorFlow, Keras, and numerous other well-known Frameworks. You could also use the Numpy library by itselfto complete it. Filters are used for feature extraction. Every selected filter needs to perform a unique function in order to produce the appropriate prediction class. The features are eliminated via convolutions, and the parameters are eliminated by the addition of pooling layers. The information from the other levels is gathered, flattened, and sent to the output layer to calculate the number of classes. The output layer is also entirely interconnected. For determining the Mean Square Loss, the output produced is compare to the error, and the loss function is chosen.

2.4 VGG 19(VisualGeometryGroup) CNN+ has 19 levels in all. The input to ii, which creates the matrix (244,244,3), is a fixed-size RGB image with a size of (244,244). The spatial resolution is achieved by applying spatial padding and Max Pooling with stride 2 over a 2*2 pixel window; the kernel's initial scaling was 3*3 with a stride size of 1 pixel. Three completely connected layers were introduced, the first two of which had a total of 4096 channels each and the third of which had 1000 channels. The classification of the ImageNet Scale Visual Recognition Challenge (ILSVRC) is done with a soft max feature as the top layer for assessment reasons.

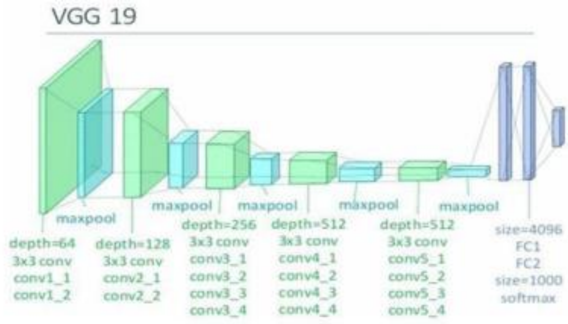

Fig 5: VGG 19 architecture

V.CONCLUSIONS

Cervical cancer is one of the awful diseases that is currently common and screening frequently requires a drawn-out clinical approach. ML can offer a high strategy for accelerating the diagnosis process. Therefore, it is more practical to use computer vision technology to get the right results. As there is no human involvement, the outcomes are more precise. In this case, the machines are trained to deliver the best results for every user input. One of the most straightforward solutions to the data problem is the use of convolutional neural networks (CNN). It requires less physical effort and is more effective.

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